Robust Design: An Image Analysis Tool for Analyzing Information Loss Caused by Viewers and Environments

Sung Soo Hwang(✉)

School of Computer Science and Electronic Engineering,
Handong Global University, Pohang, Republic of Korea
sshwang@handong.edu

Abstract. For the efficient expression of information, graphic designers utilize colors or various combinations of colors. Unfortunately, the information expressed by colors may be lost depending on the characteristics of viewers and environment. This paper presents an image analysis algorithm which informs designers of these information losses and helps them to produce graphic designs that are robust to various situations. The proposed method first generates the simulated model of the design and applies the equivalent segmentation algorithm to the original design and the simulated model. As a result of segmentation, each image is partitioned into several groups. And by measuring the ratio between the number of groups in the original design and that in the simulated model, the information loss can be estimated. With the proposed algorithm, designers can easily perceive that the use of certain colors or combination of colors should be avoided to minimize the information loss.

Keywords: Universal design · Information loss measurement · Image segmentation

1 Introduction

For the efficient expression of information, graphic designers utilize colors or various combinations of colors. Utilizing colors is a reasonable choice, because for general users in general environment, it gives a large amount of information and insight. Unfortunately, the information expressed by colors may be lost depending on the characteristics of viewers and environment. This can happen when viewers are color blind, colored graphic designs are printed in gray-scale, and designs are displayed in colored illumination, and so forth. Figure 1 shows several examples of these information losses. When it is viewed by a person with protanopia, a graphic design which is easy to notice such as Fig. 1(a) becomes a vague one. Similarly, a graphic design which contains lots of information such as Fig. 1(c) becomes meaningless when it is printed as in gray-scale. Even though a certain amount of information loss is inevitable, it can cause serious problems if the information expressed by colors is critical. Hence, it is desirable, during the design process, to notify designers that the use of certain colors should be avoided to minimize the information loss.

A. Marcus (Ed.): DUXU 2016, Part III, LNCS 9748, pp. 159–166, 2016.
DOI: 10.1007/978-3-319-40406-6_15

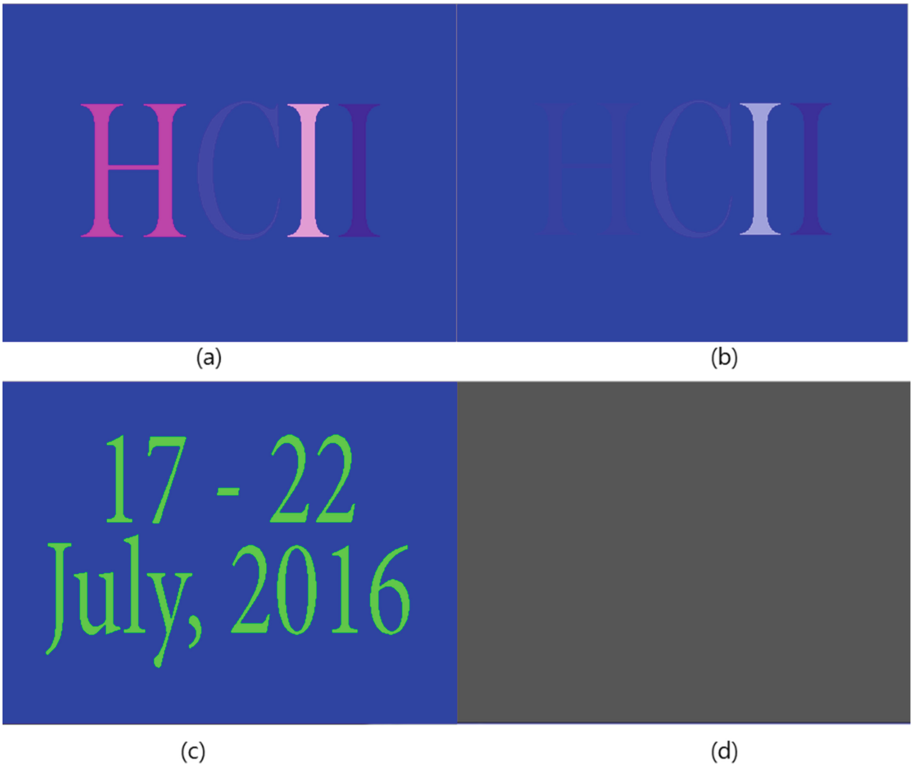

Fig. 1. Examples of information losses caused by viewers and display condition. (a)(c)Original graphic design (b) Graphic design (a) viewed by a person with protanopia (d) Graphic design (c) when printed in gray-scale

In order to prevent graphic designers from using several colors or combinations of colors that causes serious information losses, the information loss depending on the characteristics of viewers and environments should be estimated beforehand. This can be achieved by generating the simulated models of an original graphic design first, and visually checking each simulated model. A similar platform is currently provided by Adobe Systems Inc. [1]. They only consider the information losses caused by color blindness, and they let graphic designers preview their arts in the same way that a colorblind individual would see it. They also let graphic designers adjust colors in their original arts while seeing how the changes impact the color blindness view. However, information loss can happen not only when viewers are color blind but also when display environment is unusual. Hence, it can be tedious to test every graphics designs since there can be lots of cases graphics designers should consider. Moreover, the platform provided by [1] does not measure the quantitative information loss. Thus, among several graphic design candidates which are designed to minimize information losses, a graphic designer should subjectively select one.

To deal with these problems, this paper proposes an image analysis tool which estimates information losses caused by viewers and display environments. In many cases, the impression of colors is related with providing subjective feelings to viewers, whereas the contrast of colors is related with providing objective information. Hence, when the contrast of colors in a graphic design is reduced, it usually causes information losses. Therefore, the proposed method measures information loss by measuring the reduction of color contrast. The main characteristic of the proposed method is that it automatically and quantitatively estimates information losses caused by various situations. For these reasons, the proposed method can help graphics designers achieve *robust design*: a graphic design that critical information is preserved regardless of viewers and environments.

This paper is organized as follows. In Sect. 2, the proposed method is explained. In Sect. 3, the proposed method is evaluated by several graphic designs. And I conclude in Sect. 4.

2 The Proposed Method

2.1 System Overview

Figure 2 illustrates the overview of the proposed method. The proposed method first generates a simulated model of the design. Thereafter, the equivalent image segmentation algorithm is applied to the original design and the simulated model. As a result, the original design and the simulated model are partitioned into several regions. Finally, the number of groups in the original design and that in the simulated design are compared to estimate the information loss.

Among a variety of situations which leads to information loss, I focus the case when viewers are protanopic, and color graphic designs are printed in gray-scale (gray-level printing). To generate the simulated model in case of users being color blind, simulation model proposed by H. Brettel *et al.* is used [2]. Gray-level image is generated by taking the average of R, G, B color components.

2.2 Simulated Model Generation

As mentioned, simulated model for protanopia is generated by using the method proposed in [2]. For the completeness of the paper, I briefly explain the method. Normal color vision is trichromatic and it is initiated by the absorption of photons in three classes of cones. The peak sensitivities of each cone is different, i.e., one type of cones is sensitive to long-wavelength (L), one type of cone is sensitive to middle-wavelength (M), and the other is sensitive to short-wavelength (S). Therefore, any color stimulus can be specified by three cone responses and all colors visible to the color-normal observer are included in a three-dimensional color space. For dichromatic observers, however, any color stimulus is initiated by two cone responses, and all colors that they can discriminate are included in a two-dimensional color space.

Based on this fact, H. Brettel et al. proposed an algorithm to imitate for the normal observer the appearance of colors for the dichromat. First, they represented a color

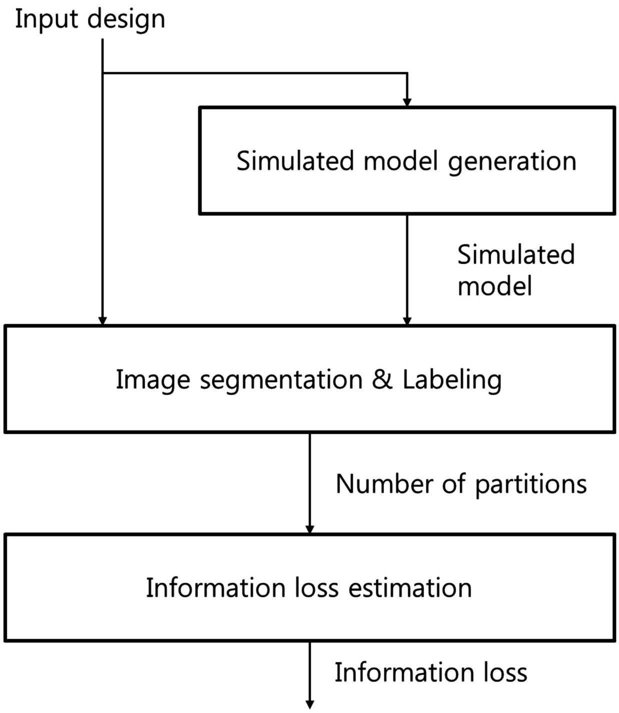

Fig. 2. The overall system of the proposed method

stimuli as vectors in a three-dimensional LMS space, *i.e.,* a color represented in RGB color space is represented in LMS space. Then, the algorithm replaces each stimulus by its projection onto a reduced stimulus surface defined by a given type of dichromat. Finally, the reduced stimulus surface is again transformed into RGB color space.

For instance, to imitate color appearance for a person with protanopia, a color stimulus Q represented in RGB color space is transformed into LMS space as (1).

$$\begin{pmatrix} L_Q \\ M_Q \\ S_Q \end{pmatrix} = \begin{bmatrix} 0.1992 & 0.4112 & 0.0742 \\ 0.0353 & 0.2226 & 0.0574 \\ 0.0185 & 0.1231 & 1.3550 \end{bmatrix} \begin{pmatrix} R_Q \\ G_Q \\ B_Q \end{pmatrix} \tag{1}$$

Then by using Eq. (2), a color stimulus Q in LMS space is projected onto the reduced stimulus surface for protanopia.

$$\begin{pmatrix} L'_P \\ M'_P \\ S'_P \end{pmatrix} = \begin{bmatrix} 0 & 2.02344 & -2.52581 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} L_Q \\ M_Q \\ S_Q \end{pmatrix} \tag{2}$$

Finally by using Eq. (3), it is again transformed into RGB color space.

$$\begin{pmatrix} R' \\ G' \\ B' \end{pmatrix} = \begin{bmatrix} 0.0809 & -0.1305 & 0.1167 \\ -0.0102 & 0.0540 & -0.1136 \\ -0.0003 & -0.0041 & 0.6935 \end{bmatrix} \begin{pmatrix} L'_P \\ M'_P \\ S'_P \end{pmatrix} \quad (3)$$

To generate a simulated model for gray-level printing, the intensity of each color component is generated as (4).

$$Y = \frac{R + G + B}{3} \quad (4)$$

Figure 3 illustrates simulated models for protanopia, and gray-level printing. Even though this paper deals with protanopia and gray-level printing, generating simulated models for another types of dichromat is straight-forward by using the method proposed in [2].

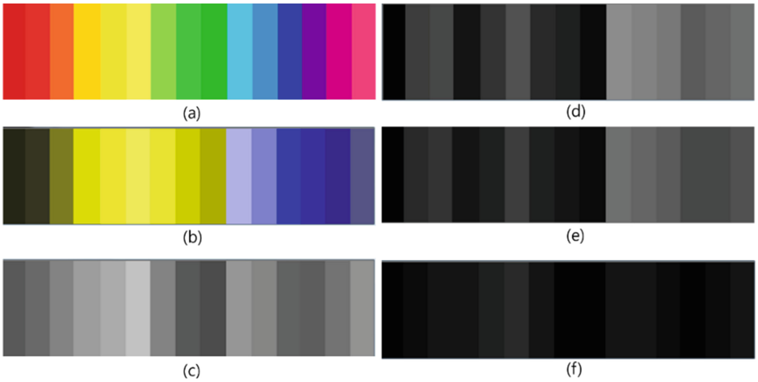

Fig. 3. Simulated model generation and segmentation results. (a) original graphic design (b) simulated model for protanopia (c) simulated model for gray-level printing (d) segmentation result of original design (e) segmentation result of (b) (f) segmentation result of (c)

2.3 Image Segmentation and Labeling

As a second step, the original graphic design and the simulated model is partitioned into several regions. A variety of researches have been conducted on image segmentation and arbitrary segmentation can be used. However, color thresholding is used in this paper for the simplicity of the algorithm. First, we uniformly quantize each color component into multiple levels. When a quantization step is set to 8 and the range of the intensity of each color component is 256, then each color component is divided into 32 levels. As a normal color consists of three color components, this makes 32,768 levels. And a color in a pixel is assigned to a certain level depending on its color components. Hence, colors that fall into the same level are considered as the same color.

For labeling (i.e., counting the number of regions in a design), a blob counting method proposed in [3] is used. Figure 3 also illustrates the result of segmentation for the original design and the simulated model.

2.4 Information Loss Estimation

Finally, the information loss of the original graphic design is estimated. As a result of segmentation, each image is partitioned into several groups. Even though equivalent segmentation method is used, as Fig. 4 illustrates, the number of groups is different and the number of groups in the simulated model tends to be smaller than that in the original design. This is because some colors become undistinguishable to protanopic, and in gray-level printing. Thus, by measuring the ratio between the number of groups in the original design and that in the simulated model, the information loss can be estimated.

Let N_O, N_S be the number of the segmented regions in the original design and the simulated model, respectively. When the number of segmented regions differs, information loss is estimated to be occurred, and it is computed by Eq. (5).

$$\text{Information Loss} = 1 - \frac{N_S}{N_O} \tag{5}$$

3 Experimental Results

The proposed method is evaluated by two types of graphic designs. Each type has 3 graphic design candidates, and each candidate contains the identical information with the same shape, but with different combination of colors. The left column of Fig. 4 shows the graphic designs used for the experiment. For the segmentation, the quantization step size was set to 8.

Figure 4 also shows the generated simulated model for each graphic design; the middle column for a person with protanopia and the right column for gray-level printing. And Table 1 describes the information loss for each graphic design estimated by the proposed method. As Fig. 4 and Table 1 indicates, the quantitative measurement of information losses estimated by the proposed method is coherent with the subjective measurement of information losses. For instance, the letter 'H' and the letter 'I' in design 1 becomes invisible when it is viewed by a person with protanopia and gray-level printing, respectively. In this case, the proposed method informs the designers that the possible information loss for each case is 0.25. In case of design 2, it is still distinguishable when it is viewed by a protanopic person, but it loses whole information when it is printed as gray-level. The proposed method still shows coherent results, *i.e.*, it analyzes that information loss for protanopia and gray-level printing is 0 and 1, respectively. Based on this information, designers can choose one design among several candidates that is robust to various viewers and environments, without personally checking the simulation results. In this experiment, choosing deigns 3 and design 5 is reasonable.

Fig. 4. Simulation results of various graphic designs (a) original graphic designs (b) simulated models for a person with protanopia (c) simulated models for gray-level printing

Table 1. The estimated information loss of each graphic design

		Information loss	
		Protanopia	Gray-level printing
Type 1	Design 1	0.25	0.25
	Design 2	0	1
	Design 3	0	0.25
Type 2	Design 4	0	1
	Design 5	0.3	0
	Design 6	0.8	0

4 Conclusion

In this paper, an image analysis algorithm is proposed which informs the designers of information loss of their design when viewed by certain viewers and certain environments. Simulated models of the original design are generated and a simple segmentation algorithm is applied to the simulated models and the input graphic design. By analyzing the number of segmented groups in each image, the information loss is finally estimated.

As the proposed method automatically provides designers with quantitative measurement of information loss, designers do not need to personally simulate their designs. Hence, I believe that the proposed method can ease the difficulties of generating robust design; a graphic design that critical information is preserved regardless of viewers and environments.

As future works, a suggestion algorithm which provides designers with possible solutions to minimize the information loss will be studied.

References

1. http://blogs.adobe.com/adobeillustrator/2009/04/new_tools_for_color_making_you_1.html
2. Brettel, H., Viénot, F., Mollon, J.D.: Computerized simulation of color appearance for dichromats. J. Opt. Soc. Am. **14**(10), 2647–2655 (1997)
3. Gonzalez, R.C., Woods, R.E.: Digital Image Processing, 3rd edn. Pearson, Upper Saddle River (2008)